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PRELIMINARY REPORT ON EDGE DETECTION METHODS AND ITS APPLICATION IN EARTHQUAKE RESEARCH

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Abstract: In this study, we develop an procedure to predict displacements causing by earthquakes at strong motion recorder sites without the use of experts' opinion. The algorithm combines methods from signal process and edge detection. We adopt methods to filter noise and detect the jumps in the strong motion data, then determine the baseline and integrate the data to find the displacement.

A set of strong motion records of earthquakes that occurred in Taiwan is used to test the algorithm. The results will be compared to the near by GPS records and prior study [7]. Because of the loss of experts' opinions, the result may seem to have larger errors. However, the purpose of this algorithm is to create a general process that can efficiently predict any displacement regardless the location of the strong motion. Therefore, we will tolerate a larger margin of error when comparing the computing results and the GPS records.

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1. Introduction

Earthquakes cause damages in many different ways. Especially in the urban area, building collapse causes huge amount of life and financial loss. Building collapse is usually caused by surface deformation. Thus, if surface deformation can be predicted, it will be useful in reducing life and financial loss.

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Digital accelerographs record acceleration data at the sites. In geosciences field, it is also called strong motion records. Coseismic deformation can be recovered easier with the instruments recording six-component (three rotations and three translations) than with the instruments recording three translational components. At this point, majority of instruments in places are still three translational. Moreover, if the coseismic deformation occur at the accelerograph site, integrating acceleration data will result in unreasonable result. Furthermore, since the strong motion data is typically non-smooth and has many location-dependent issues, many studies are often rely on experts' opinions in part of the process. This makes it difficult to develop an automatic algorithm for predicting displacement.

There have been discussions on how to recover coseismic deformation from strong motion records since 1976. Applying baseline correction on the strong motion records was combined with different techniques to recover the displacement, such as, by Iwan et al [5], Chiu [4], and Boore [2]. Boore [2] especially surveys various schemes for recovering final displacements using the strong-motion records.

With the goal of creating a completely automatic recovering displacement process later on, this preliminary report shows the result from a process combining Kalman-filter, edge-detection method, and baseline correction. In Section 2, brief discussion on Kalman filter and edge detection method will be discussed. The numerical results and conclusion will be discussed in Section 3.

2. Data Processing

Figure 1 shows an acceleration model and a corrected displacement model used in many related papers. However, the process of determining T1, T2, and T3 has been an issue of discussion. There are two main reasons that explain the difficulty of determining those three points through most of traditional applied mathematics techniques. First, the record are extremely unsmooth. Due to the unsmoothness, it is almost impossible to consider a differentiable function even for a part of the original data. Secondly, for each earthquake, many location-dependent characteristics may have changed the property of acceleration data. The deformation may be different in different locations even if they have the exactly same strong motion data. Most related papers relied on the experts' decision on determining one or more of those 3 points.

Next, we will discuss the adopted methods, a Kalman filter and a edge

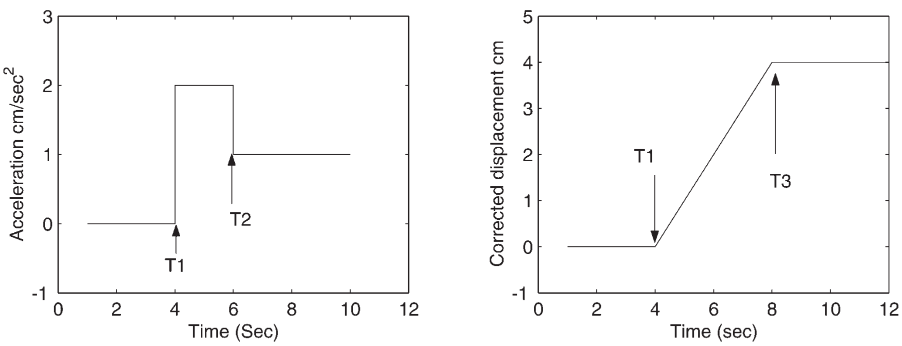

Figure 1: Acceleration and corrected displacement model

detection method, separately. Afterward, we will give a description of the process used in this study.

2.1. A Kalman-Filter

The Kalman filter [6] is a set of recursive equations to estimate the state of a process. In general, those equations fall into two groups: time update and measurement update. Time update equations are responsible for predicting the state based on the prior data. Measurement update equations are responsible for correcting or improving the estimate from the time update equations. Our approach uses the idea of estimating a random constant. The filter is also known to be powerful because of its estimations of states even when the precise nature of the model is unknown. The approach is based on that the strong motion data will be stabilized after a period of time as it is shown in Figure 1. If we provide the data after T1, the result of Kalman filter should estimate the level of the second horizontal line in the acceleration model of Figure 1.

2.2. Edge-Detection Method

The edge detection method is also called jump detection. The article [1] proposes a new edge detection method. This method is based on a local polynomial annihilation techniques. We will provide one-dimensional case below. Let f be a piecewise smooth function only known on S which is a set of discrete points. If the function $[f](x)$ is defined as $[f](x) := f(x+) - f(x-)$, it is clear that

$[f](x) \neq 0$ if f is discontinuous at x, $[f](x) = 0$ if f is continuous at x. Therefore, while constructing an approximation $L_m f$ of $[f]$, $L_m f$ should approach zero for any points away from discontinuities. For each x, $L_m f(x)$ is computed as follows:

$$L_m f(x) = \frac{1}{q_m(x)} \sum_{x_j \in S_x} c_j(x) f(x_j),$$

where $c_j(x)$ is determined by the solution of the system

$$\sum_{x_j \in S_x} c_j(x) p_i(x_j) = p_i^{(m)}(x),$$

$\{p_1, p_2, \ldots, p_{m+1}\}$ is a basis of $\prod_m$, the polynomial vector space with degree less than or equal to m, and $q_m(x)$ is the normalization factor. It is shown in [1] that $L_m f(x)$ converges to zero away from the jump discontinuities of f. This method is shown to be numerically cost efficient.

2.3. An Algorithm

The process starts with the determination of $T1$. The choice of $T1$ is the same with the Wu et al [7] when the magnitude of acceleration is greater than 50 cm/sec^2. Consider the acceleration data after $T1$. With various choices of standard deviation between 0.01 and 0.5, we obtain the results from the Kalman filter. Then we apply the edge detection method to the filter results. Thus the edge detection method provides us a range of possible $T2$. By using the lowest and largest $T2$ as breaking points, we apply the baseline correction on the acceleration data. Finally, we apply numerical integration on corrected acceleration data to obtain velocity and the displacement. After we obtain the displacement, we use the least square approximation to approximate the stabilized level of the displacement.

3. Numerical Results and Conclusion

The result is only on east-west direction. The distances between GPS and the accelerograph sites are ranged from 40 meters to over 1000 meters. The following table shows the result compared with Wu et al [7] and nearby GPS result in terms of ratio.

EW	Wu	GPS	Algorithm1	Ratio(Wu)	Ratio(GPS)
tcu056	46.1	59.1	46.95	1.02	.79
tcu060	62.	55.8	76.77	1.23	1.38
tcu074	-193.8	-187.7	-162.36	.84	.86
tcu076	87.3	88.2	94.92	1.09	1.08
tcu079	-71.9	-151.9	-153.71	2.14	1.01
tcu102	87.5	66.3	79.2	.91	1.19
tcu120	70.8	70	98.29	1.39	1.4
ttn001	2.6	1.2	1.29	.5	1.08
ttn004	-.6	-.4	-.89	1.48	2.23
ttn014	6.6	8.3	5.06	.77	.61
ttn051	3.4	3.1	3.4	1.0	1.10

With experts' opinions in determining $T3$, the method proposed by Wu et al [7] shows the ratios between 0.78 and 1.41. In our study, although the data set is relatively small, the majority of results in this group with the ratios between 0.5 and 1.5. This result indicates the potential of developing an automatic algorithm for predicting displacements.

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